BMC Neuroscience

BioMed Central

Poster presentation

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Sharpening projections

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from Eighteenth Annual Computational Neuroscience Meeting: CNS*2009
Berlin, Germany. 18–23 July 2009

Published: 13 July 2009

BMC Neuroscience 2009, **10**(Suppl 1):P214 doi:10.1186/1471-2202-10-S1-P214

This abstract is available from: http://www.biomedcentral.com/1471-2202/10/S1/P214

It is known that neuronal arbors can project roughly topographically from their source to their target area [1]. However, developmental rules in the cortex often provide only roughly reciprocal connections through chemical cues governing the physical location of distant axonal arbors, leaving open the question of whether more precise reciprocal connectivity is possible in these cases [2,3]. We address this question of whether it is possible for a biologically plausible learning rule to adjust the synaptic weights so that the projection effectively becomes more precise than the anatomy alone provides. We have discovered a biologically plausible set of learning rules that can adjust the synaptic weights so that precisely reciprocal ones are strengthened while others are weakened, thus effectively increasing the specificity of the projections.

The question introduced above can be generalized to any number of areas connected in a feed-forward cycle with feedback only coming as a result of information traveling around the entire cycle. We examined the cases of two or three areas connected in a directed cycle. Each area was represented by a pool of linear threshold units having a sigmoidal threshold function, with inter-area weights initialized to random weight matrices, corresponding to the worst case of a neuronal arbor completely covering the target area. For the dynamics of the unit activities and the weights, we combined three techniques that plausibly have biological counterparts: winner-take-all circuitry [4,5], activity regulation [6], and Hebbian learning [7,8]. On the shortest time scale, winner-take-all circuitry within each pool ensures that the current configuration of activity consists of a clearly localized region of activation. On an intermediate time scale, activity regulation within each unit dampens the likelihood for units to win the winner-take-all competition if they have been highly active but increases their chance to win if they have been inactive, thereby enforcing fair use of the units. On the slowest time scale, Hebbian learning increases the weights along active cycles, making them more likely to recur. Over time, this encourages specific cycles to be strengthened, while the activity regulation ensures that these specific cycles cover all of the units in each pool.

Depending on the combinations of parameters used, it was possible to generate two kinds of reciprocal connectivity. In the first kind, strong precise reciprocal connections developed, with weaker strengths for connections close to being reciprocal, and much weaker connections elsewhere. In other words, the product of the weight matrices was a blurred identity matrix. In the second kind, each area partitioned itself into distinct subgroups, and then the subgroups formed fully connected cycles. In this case, the product of the matrices was a crisp block identity matrix. Both forms of connectivity can be useful within larger artificial architectures and we claim they could easily occur in brains.

Acknowledgements

The authors, who are listed alphabetically, would like to thank ETH Research Grant ETH-23 08-1 and EU Project Grant FET-IP-216593.

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